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Making smart meters smarter the smart way

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Making Smart Meters Smarter the Smart Way

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Abstract
We report first results from a large scale randomized control trial of different forms of energy consumption feedback facilitated by smart meters and smart phone feedback apps. Nearly 40,000 customers of a large energy retailer in the UK were exposed to either very basic feedback apps - i.e. simply giving consumers access to monthly energy consumption - or more advanced feedback involving peer group comparisons as well as dis-aggregation of total electricity consumption. We find that more advanced feedback can lead to an average consumption reduction of nearly 4% (Intent to Treat). Taking into account that a large number of customers never sign in to any feedback apps suggests that the reduction effect among customers that do sign in is up to 12%. The smart meter installation was implemented by different installation firms across our sample and we find the reduction effect only for one customers of one installer who displays higher capabilities along a number of metrics. This could suggest that achieving energy preservation objectives does not only depend on the technology involved but also on the capabilities and skills of firms installing those technologies. In the UK, smart meters are by default installed with In Home Displays (IHD) that provide real time feedback on energy use. Some of the customers in our sample did not receive an IHD and we explore if this had any impact on the consumption reduction effect described above. Customers with (and without) IHD comprise a self-selected sample so we have to be careful in drawing causal conclusions. However, we do not find any evidence that any energy reducing effect is contingent on IHDs.

Key words: behavioural intervention, household energy demand, randomised controlled trial, information
JEL Codes: D12; Q48; Q54

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1 Introduction

By 2020 - according to EU legislation - most households in Europe should be "smart" metered.[1] What effect will this increase in smart metering have on consumers, electricity consumption, and electricity markets more broadly?

The answer to this question this depends to a large extent on whether and how consumers interact with the meters. In the UK, energy producers are mandated to both install smart meters and provide so-called In Home Displays (IHDs) that provide real-time energy consumption information to customers in the hope that such information will induce energy-saving behavioural changes. However, energy firms have insisted that similar, if not stronger, behavioural changes could be achieved by providing energy consumption feedback via a smart phone apps, which would dramatically reduce costs relative to universal provision of IHDs.

We test this claim using a randomized controlled trial (RCT) wherein customers who were invited to receive a smart meter installation were divided into 4 intervention groups with the following characteristics:

1. **IHD:** IHD and basic app reporting monthly energy consumption;

2. **SP APP:** No IHD and a more advanced app including up to daily energy consumption information;

3. **ONZO:** No IHD and an even more advanced app providing comparisons with other customers and demand dis-aggregation. This option is named after ONZO a software and data analytics company that provided this functionality.[2]

4. **CAD:** Installation of a so-called consumer access device (CAD) that provides higher resolution remote energy monitoring. This allows providing real-time consumption information via smart phone app.

Since the electricity utility contracted four different installers, a few complexities arose during experimental implementation. Each installer is typically focused on a particular part of the country. In order to simplify the task for these installers, any one installer would only ever deliver two treatment options: one non-IHD option and the default IHD option. Additionally, the ONZO non-IHD alternative was rolled out by two different installers. These elements raise two potential issues.

First, the effective treatment that participants receive is an interaction of a particular treatment (e.g., ONZO app) with a particular installer. Hence, if we find differential responses to treatment, it could be (partially) attributable to the inherent features of the feedback app or the manner in which a particular installer administers the treatment. For instance, installers may vary in their ability to explain the feedback app to customers. Second, it could be the case that any discernible effect is specific to the population of customers assigned to any particular installer, creating the illusion of an 'installer effect' when in fact the effect is driven by characteristics of the sub sample treated by the installer.

[1] This is part of the legislation to create a joint energy market across the EU; see e.g. http://ses.jrc.ec.europa.eu/smart-metering-deployment-european-union

[2] urlhttp://onzo.com/

An additional problem that emerged during the trial is that in most cases a mixed treatment was administered, i.e. customers that were supposed to receive an advanced software treatment with *no* IHD were in many cases provided with an IHD nonetheless. Two factors contributed to this contamination. First, customers having heard about IHDs from friends or advertisements then demanded the devices from the installers and, in this case, installers were instructed to give in to customers' demands. Second, in a number of cases, IHDs were simply given to customers by mistake or because installers ignored instructions. This non-compliance implies that we cannot fully ascertain whether any differences between treatment and control groups result from the effect of advanced apps alone or whether they are the result of an interaction or complementarity between software and IHD effects. Of course, we can analyze whether there are differences in effects between treated with or without IHD. However, we cannot rule out that any such differences are driven by self-selection into those groups. That said, we can search for evidence of such selection bias on the basis of historic consumption data. This issue is of some urgency as one of the motivations for conducting the RCT was the provision of evidence under the smart meter derogation. The smart derogation was a temporary exemption granted by the UK government to some energy companies from the requirement to provide IHDs in order to examine if IHDs are a necessary requirement of behavioural changes by customers. [3]

This document provides some first results derived from the data that emerged from the experiment. We will be obtaining more data in the near future, as the experiment is ongoing. As such, these results are subject to change.

Our findings so far can be summarized as follows. There seems indeed to be a causal effect of the ONZO software treatment, though only in conjunction with one of the installers tasked with rolling out this treatment. Our initial estimates suggest that on average electricity consumption could have reduced by up to 4% as a consequence of receiving the advanced ONZO app. This effect occurs for the installer who overall has a better record in delivering Treatment 3 as instructed (i.e. without providing an IHD). It is therefore possible that this installer (let's call her Installer 3) is simply more competent and, therefore, better at training her customers to understand the functionality of the ONZO app.

In the case of other treatments or other installers, we did not find significantly negative effects on energy consumption. As for CADs, we found a positive (though insignificant) effect on consumption, which could be related to serious difficulties in the roll-out of CADs resulting in customers' not receiving any treatment. Hence, it could be the case that the CAD-assigned treatment group is our best estimate for what happens to customers without IHD nor software.

[3] In hindsight, it would have been advisable to adjust the software treatments in cases where for whatever reason an IHD was given out so that an IHD would always come in conjunction with the basic software treatment from option 1 above.

In order to address the derogation question—i.e. can a given reduction be achieved with app-only treatment, obviating the need to supply customers with costly IHDs?—we examine if there is a difference between non-IHD assigned customers that have not received an IHD (non-IHD, non-IHD) and customers that ended up with an IHD nevertheless (non-IHD, IHD). For installer group 3 we do not find a significant difference between these two groups and the point estimates are of similar size. We also do not find a significant difference between these two types of customers in their historic energy consumption. Hence, we can be somewhat confident that there is no systematic selection going on between these two groups and, therefore, it would seem that the ONZO effect is not contingent on having received an IHD. However, the statistical test lacks power at present, so it will be crucial to gain more observations from the ongoing trials before drawing strong conclusions.

2 Related Literature

Research in behavioural science has explored the effects of providing energy consumption feedback. While some experiments show that feedback provision can in some cases lead to energy reductions in the residential sector (Allcott (2011)) the achievements of various experiments vary widely. There have been several trials of feedback, but it is difficult to compare interventions given they differ in the feedback mechanisms they rely on (Karlin et al. (2015)) as well as in their design and structure (Faruqui et al. (2010)). A meta-study by Delmas et al. (2013) find the average effect of feedback to be 7.4%, ranging from 55% reduction to an increase of 18.5% in one experiment. Faruqui et al. (2010) also find that the effect of a simple In-Home-Display (IHD) in North America is on average 7%, but that customers being on prepayment schemes doubles it to 14% effect. In a different study, where the user-friendliness character of IHDs was emphasised with its users and promoted its domestication achieved a 20% reduction Chen et al. (2014). Behavioural science explains that feedback provision triggers change through two mechanisms. First the learning effect: consumers develop better knowledge about energy consumption. Second the salience effect: consumers are constantly reminded about their energy use (Lynham et al. (2016)). Energy consumption is abstract, non-sensory, and of low relevance to most individuals, so feedback emphasises its financial, environmental, and social costs and helps consumers relate to their energy use (Karlin et al. (2015)).

While information is necessary to induce behaviour change, it is not sufficient as demonstrated by trials where consumers gain knowledge and awareness about their energy usage but do not adopt sustainable behaviours (Naus et al. (2014); Frederiks et al. (2015)). Information will affect how consumers value their flexibility and comfort (Buchanan et al. (2014)). Yet, their decisions in terms of energy use also largely depend on contextual variables and personal circumstances that vary across households (Karlin et al. (2015)): these can either hinder or support energy saving initiatives, whether for environmental, social or economic reasons. It is thought that interventions could overcome contextual and personal factors by taking into account household dynamics, routines, socio-cultural norms, and structures to achieve the transition to sustainable behaviours by consumers (Buchanan et al. (2014)).

Several studies have documented the potential of a boomerang effect when the feedback mechanism is associated with descriptive norms, with consumers relaxing their habits and resting on their laurels, thus leading to increases in consumption (Schultz et al., 2017). Alternative strategies include goal comparison (citekarlin2015effects), social influence by making reference to a social leader or using public commitment (Abrahamse and Steg (2013)), or individual audits (Delmas et al. (2013)). In a paper by Chen et al. (2017)), it is shown that non-monetary messages emphasising the health and environmental benefit of energy conservation in India were more efficient in yielding energy consumption reductions than monetary information.

Finally, other studies have examined whether dynamic pricing can decrease overall energy consumption, and has been shown to be challenging (Faruqui et al. (2010)).

While the existing literature is rich in testing the impact of IHDs in different circumstances, our study is to the best of our knowledge unique in comparing their effect to smartphone app-based feedback mechanisms.

Figure 1: Sizes of the treatment groups

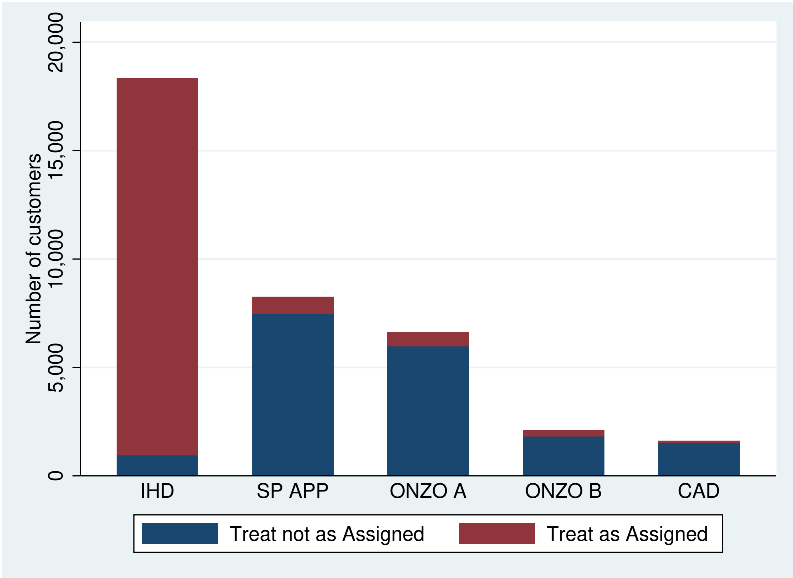
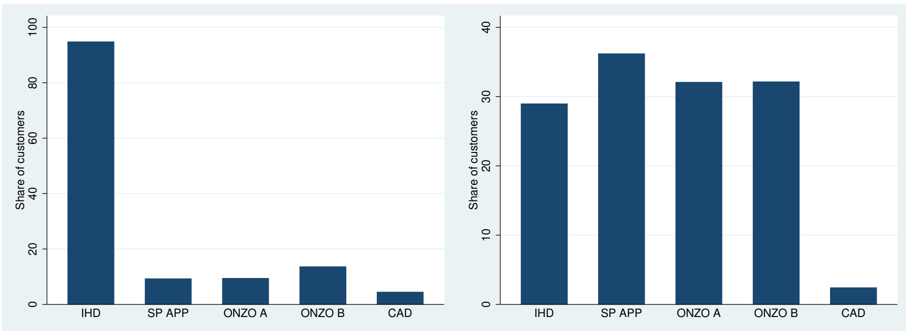


Figure 2: Share of customers with treatment as assigned across treatment groups

(a) Hardware

(b) Software



Notes: Figures are in %.

3 A first look at the data

This section describes the details of the randomised control trial and how different the groups are in terms of the data made available for our study. While customers were randomly assigned to different treatments, they did not necessarily—nor indeed primarily—end up with the treatment to which they had been assigned. Figure 1 illustrates this noncompliance by showing the proportion of participants assigned to each group that received their assigned treatment.

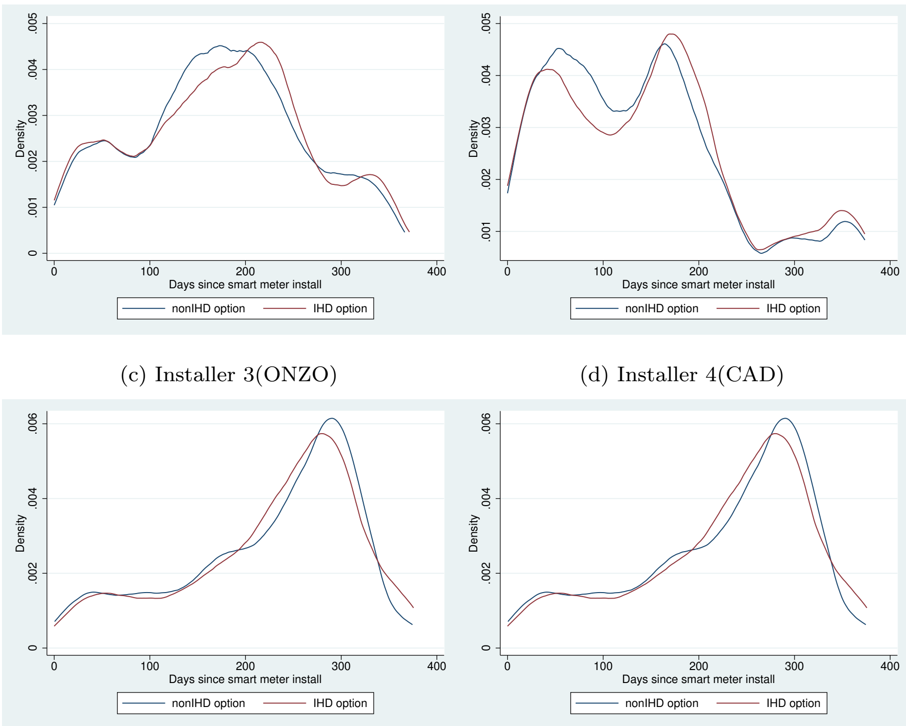
Indeed only 9.3% of customers assigned to the SP APP treatment (Installer 1) actually received this treatment without also receiving the IHD (the remaining 90.7% were given both an IHD and the SP App). For the ONZO treatment, the corresponding figure is 9.4% for Installer 2 (ONZO A) and 13.6% for Installer 3 (ONZO B). Only 4% of CAD assigned customers actually received a CAD (see Figure 2 a). One must also consider whether, once the hardware installation has been done, the customers adopt the software solution associated with their assigned treatment, i.e. downloading the ONZO/SP app. The fraction of customers that did so, albeit not necessarily without IHD, is much higher at approximately 30% for each group apart from CAD (see Figure 2 b).

Table 1 reports basic descriptive statistics, which shows that the sample is neatly split between IHD assigned and non-IHD assigned. On average these consumers use about 0.4 kW of electricity and historically have been using about 3500 kWh of electricity per year. Notice that 0.4 kW $\times$ 24 hours $\times$ 365 days = 3504 kWh. Hence, on average at least, the electricity consumption measured via smart meters seems roughly in line with historic non-smart-metered consumption estimates.

Table 1: Descriptive Statistics

variable	Treatment assignemnt	mean	sd	p25	p50	p75	p90	Obs
Average hourly energy consumption [kW]	IHD	0.43	0.31	0.24	0.36	0.54	0.77	18325
	non IHD	0.44	0.32	0.24	0.36	0.54	0.78	18582
Historic Annual Energy Consumption [kWh]	IHD	3490	2336	1977	2983	4381	6131	17616
	non IHD	3502	2424	1987	2974	4355	6145	17840

Figure 3: Total days with Smart Meter



(a) Installer 1(SPAPP)

(b) Installer 2(ONZO)

(c) Installer 3(ONZO)

(d) Installer 4(CAD)

Also note that there are no significant differences in either historic or current consumption levels on average between the different treatment groups.

Figure 3 shows density plots of how long the customers have had a Smart Meter for by the time the data was collected, i.e. the days since Smart Meter installation. This varies greatly between installer groups. Note for instance that for Installer 3 a large number of customers had had the smart meter for as much as 300 days or more at the time of data collection, whereas for Installers 2 and 1 the majority had had it for less than 200 days. The figures don't suggest that there is a systematic difference in roll out between treatment groups within a given installer which is in line with expectations: customers were randomized into treatment groups at the level of customers groups that were scheduled to receive smart meter roll outs.

4 Balance Tests

In Table 2 we report balance tests for the various treatment groups separately by running regressions of historic energy consumption on the interaction of each installer dummy with the installer's respective non-IHD assignment as well as a number of controls, as specified below:

$$Hist_c = \sum_i (\beta_{i \times nonIHD} I\{Inst_c = i\} \times nonIHD_c + \beta_i I\{Inst_c = i\}) + \beta_x X_c + \epsilon_c \qquad (1)$$

Table 2: Balance Tests

Dependent Variable		(1)	(2)	(3)
		Log of historic electricity consumption in kWh per annum		
Non IHD assignment	Installer 1(SPAPP)	-0.006	-0.001	-0.001
		(0.010)	(0.005)	(0.005)
	Installer 2(ONZO)	0.003	0.002	0.004
		(0.012)	(0.006)	(0.006)
	Installer 3(ONZO)	-0.028	0.001	-0.007
		(0.022)	(0.013)	(0.014)
	Installer 4(CAD)	0.044	0.003	-0.035
		(0.039)	(0.027)	(0.025)
Obs		35436	35436	35436
R2		0.030	0.713	0.735
Installer Controls		yes	yes	yes
Invite Month Controls		no	yes	yes
Install Month Controls		no	yes	yes
Historic Energy Quartile Controls		no	yes	yes
Installer X Invite Month X Install Month X Energy Quartile		no	no	no

where $Hist_c$ is the (log of) historic energy consumption of consumer c, i indexes installers, $I\{Inst_c = i\}$ is an indicator variable equal to 1 if consumer c is being served by installer i, $nonIHD_c$ is an indicator variable equal to 1 if a customer is randomly selected into the non-IHD treatment group, X_c is a vector of various additional control variables, and ϵ_c is an error term. If the sample is balanced for each of the installer groups we should not reject the null hypotheses that the $\beta_{i \times nonIHD}$'s are equal to zero for each of the four groups.

Column 1 of Table 2 reports a regression of equation 1 without further controls X_c. For none of the treatment groups do we find a significant difference between treatment and control group which is what we would expect given the random assignment of treatment status. Hence, there is no need to add further control variables to avoid bias. However, further control variables might be useful in making estimates more precise. In column 2 we controls for invite month (i.e. the month when the invitation to upgrade to a smart meter was sent to the customer), install month as well indicators based on the quartiles of historic energy consumption of the customer. In column 3 we add further controls by including interactions between all these variables. As in column 1 this does not lead to any significant differences between treatment and control groups. However, note that this substantially increases the amount of variation explained by the regression model (R2).

5 First stage

Before discussing the main results, we report regressions of treatment received indicators on treatment assignment in Table 3. These can be thought of as first stage regressions in an Instrumental Variables setting: a basic requirement is that treatment received is driven by our exogenous treatment assignments in a statistically significant way. In Table 3 we examine this by running regressions similar to equation 1 with various indicators of treatment receipt as the dependent variables. Column 1 reports results for a regression of an indicator for non-IHD treatment implementation on the various installer-treatment assignment interactions.[4] We see that in all installer groups non-IHD assignment is a strong driver of non-IHD treatment. However, as we could already see from Figure 1, the differences between non-IHD assigned and not assigned are not very big; for instance for Installer 1 our results imply that a customer in the non-IHD assigned group have only a 5.3 percentage point higher chance of *not* getting an IHD. Notice that the figure is larger for Installer 3 with a nearly 10% adoption rate. As discussed before the figure is very low for the CAD group, because of technical problems in rolling out CADs.

[4]Note that the indicator for non-IHD treatment adoption is *not* equal to 0 for IHD-assigned consumers, some of whom might not have received an IHD because they did not get a smart meter. Equally there is a sizable number of CAD-assigned customers who ended up—as of sampling time—with neither an IHD nor any software app.

Table 3: First stage Regressions

		(1)	(2)	(3)
Dependent Variable		Assigned treatment adoption	App Adoption	Non standard App Adoption
Non IHD assignment	Installer 1(SPAPP)	0.053***	0.048***	0.370***
		(0.004)	(0.007)	(0.005)
	Installer 2(ONZO)	0.058***	0.053***	0.350***
		(0.004)	(0.008)	(0.006)
	Installer 3(ONZO)	0.098***	0.037**	0.330***
		(0.009)	(0.017)	(0.011)
	Installer 4(CAD)	0.091***	-0.126***	0.022***
		(0.013)	(0.010)	(0.004)
Obs		35436	35436	35436
R2		0.082	0.106	0.266
Installer Controls		yes	yes	yes
Invite Month Controls		yes	yes	yes
Install Month Controls		yes	yes	yes
Historic Energy Quartile Controls		yes	yes	yes
Installer X Invite Month X Install Month X Energy Quartile		yes	yes	yes

Column 2 reports on app adoption (irrespective of how advanced the app is). We see that customers who were offered the SP APP were about 4.8 percentage points more likely to adopt an app than customers assigned to a basic app. Adoption rates are lower for CAD customers, presumably because of the roll out issues. Finally in column 3 we examine the relative likelihood of adopting a more advanced app; i.e. depending on the installer group that is the Advanced SP app or the ONZO app. Because only non IHD assigned customers have this option the numbers are vastly bigger than in column 2; i.e. more than 30% except for installer 4. Also note that because by definition the likelihood of adoption is zero for IHD assigned customers these relative probabilities are equivalent to the adoption probability or share as shown in Figure 2b.

6 Main results

Table 4 reports our main results of the effects of various types of treatment on average energy consumption as reported via smart meters. The first panel reports results in terms of the log of energy consumption. Hence we can interpret estimates as percentage impacts. Thus for example, the coefficient for Installer 3 in column 1 implies that the non-IHD assigned customers of Installer 3 use about 3.1% less power on average than Installer 3's IHD-assigned customers. While this figure is bigger than for the other installers the coefficient is not significant at either 5 or 10 percent. However, there are a vast number of factors that determine a customers energy consumption and the type of energy feedback is likely only a small influence in comparison. Hence, as suggested already in the discussion of Table 2 it makes sense to include further control variables in order to reduce the standard error of the estimates. In columns 2 and 3 we include the same control variables as in Table 2; i.e. in column 2 Invite and Install month as well as Quartile energy bands controls. This leads to a slightly lower point estimates of -2.5% for customers of Installer 3, however the effect is now significant at 10%. In column 3 we include in addition a full set of interactions between those control variables. This strengthens the significance of the results and leaves us with a point estimat of a 4.1% reduction for Installer 3 customers.

Interestingly, there is also the hint of a positive effect in the CAD group, which may actually reflect the baseline smart meter effect due to a large group of customers in this group that have neither received an IHD nor any software-based feedback solution. In other words, simply receiving a smart meter without any additional feedback mechanism may actually increase consumption, though we are underpowered to detect this result with statistical significance.

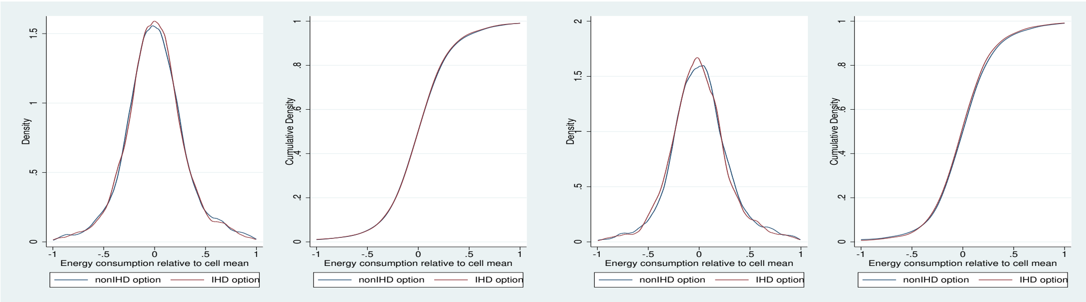
Figure 4 provides a graphical illustration of the results by showing density and cumulative density plots for every installer group. We see that in installer group 3 the density plots for non-IHD assigned customers are shifted slightly to the right. Also note that the shift occurs fairly

Table 4: Regressions of average hourly electricity consumption

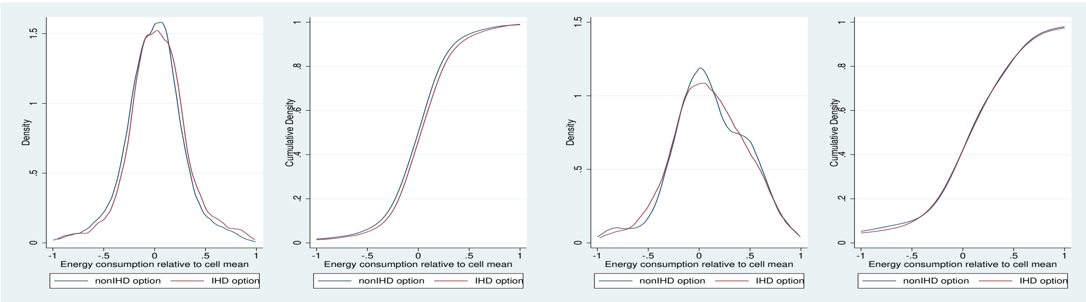
		(1)	(2)	(3)
Dependent Variable			log of average kW per hour	
Non IHD assignment	Installer 1(SPAPP)	-0.003	-0.001	-0.002
		(0.010)	(0.006)	(0.006)
	Installer 2(ONZO)	0.012	0.002	0.001
		(0.011)	(0.006)	(0.006)
	Installer 3(ONZO)	-0.031	-0.025*	-0.041**
		(0.020)	(0.014)	(0.016)
	Installer 4(CAD)	0.074*	0.043	0.009
		(0.039)	(0.029)	(0.026)
Obs		35436	35436	35436
R2		0.039	0.613	0.639
Dependent Variable			Average kW per hour	
Non IHD assignment	Installer 1(SPAPP)	-0.001	0.001	-0.000
		(0.005)	(0.003)	(0.003)
	Installer 2(ONZO)	0.011*	0.006	0.005
		(0.006)	(0.004)	(0.004)
	Installer 3(ONZO)	-0.013*	-0.008	-0.018***
		(0.008)	(0.006)	(0.007)
	Installer 4(CAD)	0.025*	0.013	0.013
		(0.013)	(0.010)	(0.009)
Obs		35436	35436	35436
R2		0.012	0.514	0.535
Installer Controls		yes	yes	yes
Invite Month Controls		no	yes	yes
Install Month Controls		no	yes	yes
Historic Energy Quartile Controls		no	yes	yes
Installer X Invite Month X Install Month X Energy Quartile		no	no	yes

Figure 4: Density plots for (log of) Electricity Consumption

(a) Installer 1 (SPAPP) (b) Installer 2 (ONZO)



(c) Installer 3 (ONZO) (d) Installer 4 (CAD)



Notes: The figure reports density and cumulative plots of density plots of energy consumption by installer group. Observations are grouped into (historic energy consumption quartile bands) x (installation month x (invitation letter sent month) cells. Density plots are for $lnEnergy - Cellaverage(lnEnergy)$.

uniformly across the support.

The lower panel of Table 4 repeats the exercise for the level of consumption (i.e. not in terms of logs). For our most general specification in column 3 this suggests that for group 3 the ONZO intervention reduced consumption by 18 Watt on average.

It is important to note that the estimates above are intent-to-treat effects, i.e. average effects for the group that has been assigned to treatment. As we have seen in the first stage regressions as well as in Figure 2, only about a third of customers are actually engaging with online apps. Hence, any effect from such apps can only affect this subset of the treated. This implies that the actual effect in consumers that are actually using the app must be much higher than 4% reductions found above. To examine this formally we can run an instrumental variable regression where the variable indicating non standard app adoption (Column 3 of Table 3) is instrumented by the random assignment into the non-IHD group. We report the results of this exercise in column 2 of Table 5. The coefficient suggests that the actual reduction for group 3 customers that actually receive the advanced app treatment is nearly a 14% reduction. In column 1 we also report the "naive" OLS estimator; i.e. we simply regress energy consumption on the indicator variable of non standard app adoption. This leads to an estimate of -0.5 for customers of installer 3; i.e. a smaller effect than in column 2. This would suggest that the kind of customers self selecting into app usage tend to be higher consumption customers.

Table 6 examines the derogation question in greater detail. In particular we examine whether there is any heterogeneity in impacts between those customers who had been assigned an advanced software treatment but also received an IHD and those who were assigned advanced software treatment and did not receive an IHD. As discussed earlier, if there are differences between these two groups we cannot necessarily conclude that they are the causal effect of either treatment as they could be due to selection effects. For instance, it could be the case that more environmentally conscious consumers—who already use less energy—are also less inclined to demand an IHD, as they perceive the IHD as a waste of resources. Fortunately, we can test this hypothesis using historic consumption data.

Column 1 starts with regressions of (log) energy consumption on the same variables as in Table 4 plus in addition a set of indicator variables (one for each installer) indicating whether a particular customer had not received an IHD ('non IHD endup'). The coefficient on these variables tells us the

Table 5: Instrumental Variable estimates of Non standard App adoption

		(1)	(2)
		OLS	IV
Dependent Variable		Log of historic electricity consumption in kWh per annum	
Advanced App Adoption	Installer 1(SPAPP)	-0.001	-0.005
		(0.007)	(0.017)
	Installer 2(ONZO)	0.002	0.005
		(0.009)	(0.022)
	Installer 3(ONZO)	-0.050***	-0.139***
		(0.016)	(0.054)
	Installer 4(CAD)	-0.168***	0.060
		(0.041)	(0.177)
Obs		35436	35436
R2		0.639	0.638
Installer X Invite Month X Install Month X Historic Energy Quartile Controls		yes	yes

difference between consumers that were assigned to not receiving an IHD and who indeed did not receive any, and those that nevertheless received an IHD. The results suggest that for Installers 1 to 3 there are no differences between IHD adopters and non-adopters. In installer group 4 consumers without IHD seem to be using substantially less energy. In column 2 we repeat the exercise using historic energy consumption as the dependent variable, which again shows that for Installers 1 to 3 there is no systematic difference between IHD and non-IHD consumers. There is a large negative effect for customers in installer group 4 though. What does this mean? Firstly, for group 3: we find that non-IHD customers are not significantly different from IHD customers in terms of current consumption. There is also no difference in their historic consumption, which suggests the ONZO effect found for this group is not dependent on having also an IHD. For group 4 on the other hand it would seem that the difference between IHD and non IHD is by and large a consequence of some form of selection of different types of customers in the two groups.

Column 3 examines the same question somewhat differently: instead of a set of indicator variables representing non-IHD assigned customers overall, we include a set of variables that are equal to one only if a customer is assigned to non-IHD but ends up having an IHD after all. As a consequence, the coefficients for non-IHD assignment and non-IHD endup represent the difference between those customers and non-IHD assigned customers. Consistent with the findings in column 1 we find a 4% reduction for non-IHD assigned, IHD received (non-IHD, IHD) customers. For (non-IHD, non-IHD) customers, on the other hand, we find a 3.8% reduction, which corresponds to the results in column 1 since 3.8=4.1-0.3. Hence, in quantitative terms there is not a big difference between either group. However, note the coefficient in the latter case is not significant. Hence, from columns 1 and 3 we can conclude that customers who did not receive an IHD in the non-IHD assigned group of installer 3 are neither significantly different from those that have been assigned to non-IHD but have received one, nor are they significantly different from IHD-assigned customers. Put differently, the evidence is not powerful enough to make a clear distinction, though quantitatively the (non-IHD, non-IHD) group is more similar to the (non-IHD, IHD) group. One important factor impacting the power of this result is the sample size both in terms of number of customers assigned to each group as well as the length of time we observe them. As the trial continues to progress, there is a good chance that we will have more reliable evidence on this front.

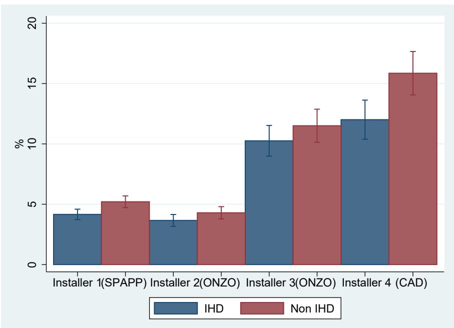
7 Conclusion and discussion

Our results provide clear evidence of a strong negative effect of some form of app-based feedback on energy consumption. We also find that this effect might depend either on the specific target population or on the way that the technology is introduced by customer-facing companies. Another issue could have to do with the length of time different customer groups have been exposed to a particular treatment. Note from Figure 3 that the installer group 3 also happens to have been

Table 6: The derogation question

	Dependent Variable	(1) log of average kW per hour	(2) Historic log of kWh		Dependent Variable	(3) log of average kW per hour
Non IHD assignment	Installer 1(SPAPP)	-0.001	-0.000	Non IHD assignment & IHD endup	Installer 1(SPAPP)	-0.001
		(0.006)	(0.005)			(0.006)
	Installer 2(ONZO)	-0.000	0.005		Installer 2(ONZO)	-0.000
		(0.007)	(0.006)			(0.007)
	Installer 3(ONZO)	-0.041**	-0.007		Installer 3(ONZO)	-0.041**
		(0.016)	(0.014)			(0.016)
	Installer 4(CAD)	0.056**	0.021		Installer 4(CAD)	0.056**
		(0.026)	(0.021)			(0.026)
Non IHD assignment & non IHD endup	Installer 1(SPAPP)	-0.008	-0.005	Non IHD assignment & non IHD endup	Installer 1(SPAPP)	-0.009
		(0.015)	(0.012)			(0.015)
	Installer 2(ONZO)	0.020	-0.012		Installer 2(ONZO)	0.020
		(0.020)	(0.013)			(0.020)
	Installer 3(ONZO)	0.003	-0.004		Installer 3(ONZO)	-0.038
		(0.028)	(0.024)			(0.029)
	Installer 4(CAD)	-0.214***	-0.253***		Installer 4(CAD)	-0.158***
		(0.049)	(0.058)			(0.051)
Obs		35436	35436	Obs		35436
R2		0.639	0.736	R2		0.639
Installer Controls		yes	yes			yes
Invite Month Controls		yes	yes			yes
Install Month Controls		yes	yes			yes
Historic Energy Quartile Controls		yes	yes			yes
Installer X Invite Month X Install Month X Energy Quartile		yes	yes			yes

Figure 5: Likelihood of half hourly readings sign up



Notes: The figure reports estimates of the likelihood that a consumer signs up for half hourly smart meter readings. We see that the propensity for this is generally low (below 15%) but that there is huge variation across different installer groups; e.g. customers of installer 2 have a less than 5% chance of signing up whereas customers of installer 3 have a more than 10% chance.

exposed to the treatment for a longer period of time. In further research we hope to understand better which of these factors is most relevant. It is also important to better understand which aspects of the advanced apps could be responsible for the effect: the relevant app (ONZO) that leads to the impact on consumption differentiates itself from the others along several dimensions, including social comparisons and demand disaggregation. This question could easily and cheaply be answered by rolling out various versions of the ONZO app even among existing smart meter customers.

One important problem of the present study in the context of the smart meter derogation is that we cannot fully ascertain the differential effects of app-only and app-plus-IHD treatment. We have some evidence to this effect from the comparison of the energy consumption of customers falling in those two groups, which suggests that there is no significant difference between them and hence the reduction in energy consumption due to ONZO treatment would seem to be independent of the availability of IHDs. However, we also find that this result is not necessarily very powerful in a statistical sense. There is hope that the power of the test will improve as more data from the ongoing trials become available.

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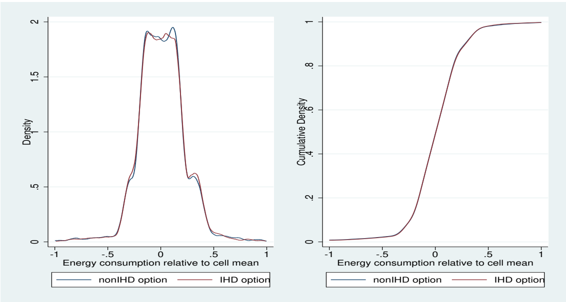
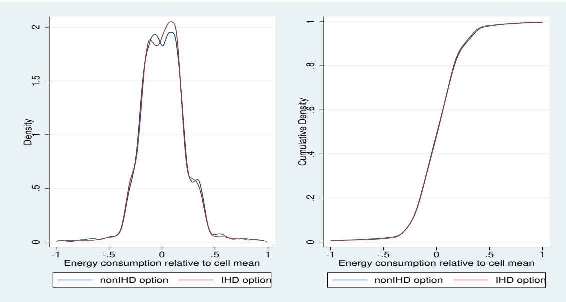
Figure 6: Density plots for (log of) Historic Energy Consumption

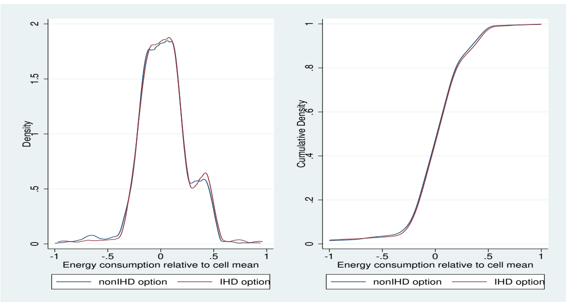
(a) Installer 1 (SPAPP)



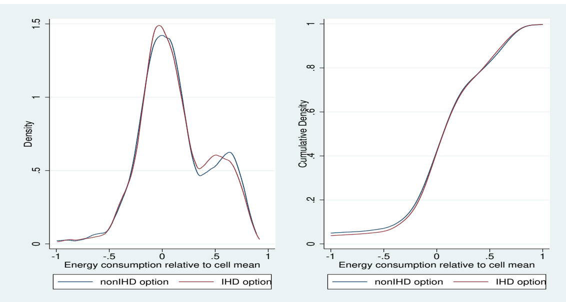
(b) Installer 2 (ONZO)



(c) Installer 3 (ONZO)



(d) Installer 4 (ONZO)



Notes: The figure reports density and cumulative plots of density plots of historic energy consumption by installer group. Observations are grouped into (historic energy consumption quartile bands) x (installation month x (invitation letter sent month) cells. Density plots are for $lnEnergy - Cellaverage(lnEnergy)$.

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